# Generation in transition: Youth transitions among native-born descendants of immigrants from Turkey

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**Publication date**
2013

# Appendix IV to Chapter 8

## 1. Latent Class Analysis

The LCA model was introduced as a method to indicate a latent categorical attitude variable, which was initially measured by dichotomous survey items (McCutcheon, 1987). Hence a number of observed response variables are measured to identify a categorical latent class variable. The main objective is to be able to cluster respondents into classes but also identify the variables that would best distinguish them into these classes (Hagenaars and McCutcheon, 2002). The LCA model has been extended to include a variety of interesting applications using not only categorical but also continuous variables, allowing for many types of outcomes (Nylund et al. 2007). Nevertheless, there are various discussions on the robustness of these alternative applications, and, as a result, the current analysis sticks to using categorical variables (ibid). In running the LCA model the current study utilized the MPlus statiscal package (Muthen and Muthen, 2006).

Variable selection was discussed in Chapter 8. Nevertheless, it is important clarify why four different analysis have been conducted. The labour market questions in the TIES survey are divided into sections; the first half is directed at those who were active and the second targets those who were inactive in the labour market at the time of the survey. Since the active and inactive respondents answered different questions, we will analyze the transitions separately for these groups, which will avoid running into too many missing values for each group. Secondly, we will also run separate analyseis for Amsterdam and Strasbourg since we argue that both cities embody distinct labour market conditions, leading to different career pathways. As a result, we will have four modelling procedures; Amsterdam Active, Strasbourg Active, Amsterdam Inactive and Strasbourg Inactive (Table 23). Within these four analyses, we will explore the latent class variable for early labour market careers for all respondents, including the native born descendants of Turkish immigrants and comparison group. We will thus have the following modelling process:

*Table 23: Selection of groups for LCA per city and activity*

| | Analysis1 | Analysis2 | Analysis3 | Analysis4 |
|---|---|---|---|---|
| | Amsterdam Active | Strasbourg Active | Amsterdam Inactive | Strasbourg Inactive |
| Second | 90 | 119 | 59 | 57 |
| Comparison | 167 | 89 | 16 | 27 |
| Total N | 257 | 208 | 75 | 84 |

Source: TIES Survey 2008

As we can see from Table 23, the distributions of second generation and comparison group are not similar across the active and inactive respondents. Second generation Turks are more present among inactive groups vis-à-vis the comparison group and this will be taken into account when interpreting the results of the analysis.

## 2. Deciding on the Number of Classes in Latent Class Analysis

There are many measures that should be taken into account when estimating the fit of a model in LCA (Nylund et al. 2007). In addition, to model statistics, the distribution of classes is crucial, as is whether classes are sound to explicate the subject at hand. Hence, even if the ideal model fit is achieved (let's say by a 2-class model), if this class did not help to understand the latent divisions, the next best fit models were sought.

Firstly, in all of the four analyses, I began with the simplest one-class solution and added more classes stepwise to see how whether the model improved. Mplus provides two "most popular" criteria that guide decisions about the number of classes; Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Muthen and Muthen, 2006). AIC is a criterion of the goodness of fit of a model that considers the number of model parameters. BIC takes into account both the number of parameters (q) and the number of observations. Recent studies show that BIC is a better measure for class enumeration (Yang, 2006). In order to decide which model fitted the data best, the models with lowest scores of AIC or BIC were taken into account (ibid). Next, Mplus reports the relative entropy, which is a measure of classification uncertainty. Relative entropy is defined between 0 and 1, and values closer to one indicate a greater certainty in classification than values closer to zero. Mplus also provides Chi-squared tests which compare the sets of observed responses with the expected responses under the model. If the test has a low p-value the model is declared not to fit (cite). Additionally, the Tech 11 test fosters the modification to the likelihood ratios test which adjusts the conventional likelihood ratio tests for n vs. n-1 classes and a P value larger that 0.05 suggests that n-1 classes are sufficient (Nylund, 2003).

Table 24 illustrates the measures for the given models. In the analysis for Amsterdam Active classes, we see that the lowest BIC, highest entropy and the best Tech 11 test significance were suggested for a two class model. However, a two class model of 26% and 74% clustered those who have a high estimated probability of working in their first jobs in the former and the rest into the latter class and did not provide much explanation for stability patterns. Hence I decided on the second best option; a three cluster model, which has the second lowest BIC measure, also a P value of 1 and an entropy measure 0.84, and which still shows great certainty on a scale of 0 to 1. In Strasbourg, the decision was much easier; both the statistical measures and the explanatory values were fulfilled by a three class model. In fact, a three-class model also fit well with the city comparison, in which the classes fostered a similar typology across settings, enabling a more meaningful juxtaposition.

In the inactive models, while BIC value was lowest for a two class model, in the chi-square test these models had zero P. Hence I selected a three-class solution which had the second lowest BIC score with P values which are higher (0.97 for Amsterdam inactive) and more acceptable (0.43 for Strasbourg inactive). According to the Tech 11 test measures while a two class solution has the best P value, the three class measures are also sufficient compared to a four class solution. Furthermore, with regard to interpretation, a 40% 60% distribution clustered all the homemakers into one class and the rest of the unemployed and inactive into another category. This did not help to make a distinction between those who were unemployed for a longer or shorter period of time. A three class distinction provided more variety and information about the different forms of inactivity in the labour market and again fostered a robust comparison across two cities.

*Table 24: Latent class measurement models fitted to data on transition trajectories*

| Model | # Classes | AIC | BIC | x2 | P | Entropy | Tech 11- P value for n-1 | Class Distributions |
|---|---|---|---|---|---|---|---|---|
| Amsterdam Active | | | | | | | | |
| Model1 | 1 | 3664.72 | 3710.86 | 2707.62 | 0.01 | -NA | NA | NA |
| Model2 | 2 | 3511.34 | 3607.16 | 1873.2 | 1 | 0.89 | 0 | 26% 74% |
| **Model3** | **3** | **3466.02** | **3611.541** | **1613.19** | **1** | **0.845** | **0.0014** | **16.7% 55.3% 28%** |
| Model4 | 4 | 3426.64 | 3621.84 | 1315.97 | 1 | 0.87 | 0.0021 | 15% 15% 51% 19% |
| Strasbourg Active | | | | | | | | |
| Model | # Classes | AIC | BIC | x2 | P | Entropy | Tech 11- P value for n-1 | Class Distributions |
| Model1 | 1 | 3014.58 | 3057.97 | 3088.43 | 0 | -NA | NA | |
| Model2 | 2 | 2895.26 | 2985.37 | 2194.11 | 1 | 0.83 | 0.0015 | 60% 40% |
| **Model3** | **3** | **2833.06** | **2969.89** | **1662.28** | **1** | **0.86** | **0.0017** | **36% 27% 37%** |
| Model4 | 4 | 2801.83 | 2985.39 | 1456.21 | 1 | 0.847 | 0.1541 | 29% 18% 29% 24% |
| Amsterdam Inactive | | | | | | | | |
| Model | # Classes | AIC | BIC | x2 | P | Entropy | Tech 11- P value for n-1 | Class Distributions |
| Model1 | 1 | 544.135 | 558.04 | 117.79 | 0 | -NA | NA | |
| Model2 | 2 | 506.394 | 536.521 | 36.153 | 0 | 1 | 0 | 40% 60% |
| **Model3** | **3** | **511.34** | **557.69** | **27.035** | **0.97** | **0.86** | **0.0276** | **40% 44% 16%** |
| Model4 | 4 | 517.581 | 580.153 | 13.091 | 0.99 | 0.89 | 0.15 | 5% 17% 35% 43% |
| Strasbourg Inactive | | | | | | | | |
| Model | # Classes | AIC | BIC | x2 | P | Entropy | Tech 11- P value for n-1 | Class Distributions |
| Model1 | 1 | 613.362 | 627.947 | 201.906 | 0 | -NA | NA | |
| Model2 | 2 | 590.809 | 622.41 | 103.007 | 0 | 1 | 0.0009 | 40% 60% |
| **Model3** | **3** | **577.25** | **625.866** | **43.746** | **0.43** | **0.825** | **0.01** | **37% 30% 33%** |
| Model4 | 4 | 585.092 | 650.724 | 32.356 | 0.64 | 0.849 | 0.3083 | 37% 30% 6% 27% |

Source: TIES Survey 2008

*Table 25: Transition Trajectories by education level*

| | Amsterdam | | | Strasbourg | | | |
|---|---|---|---|---|---|---|---|
| | Lower Sec.Voc. (VMBO) | Post-Secondary (HAVO/VWO/MBO) | Tertiary Edu (HBO/Uni.) | LowerSec. (College) | Vocational Post. Sec.(CAP/BEP) | Academic Post Sec.(BAC) | Tertiary Edu (BTS/Uni/CPGE |
| Early Careers | 22% | 30% | 42% | 11% | 16% | 38% | 36% |
| Stable Careers | 24% | 36% | 42% | 20% | 19% | 22% | 15% |
| Shifters | 11% | 10% | 4% | 28% | 35% | 31% | 32% |
| Inactive | 21% | 13% | 1% | 10% | 13% | 6% | 8% |
| Stagnant | 18% | 9% | 7% | 17% | 5% | 0 | 1% |
| In-Transition | 4% | 3% | 0.04 | 14% | 13% | 3% | 7% |
| N | 72 | 111 | 149 | 123 | 63 | 32 | 74 |

Source: TIES Survey 2008

*Table 26: Transition Trajectories by age group*

| | Age Group 18-22 | | Age Group 23-29 | | Age Group 30+ | |
|---|---|---|---|---|---|---|
| | Amsterdam | Strasbourg | Amsterdam | Strasbourg | Amsterdam | Strasbourg |
| Early stable | 27.3% | 30.4% | 21.1% | 27.7% | 20.5% | 1.0% |
| Stable | 20.5% | 0.0 | 40.9% | 19.7% | 53.8% | 48.5% |
| Shifting | 11.4% | 16.1% | 11.1% | 26.3% | 16.2% | 32.3% |
| Inactive | 9.1% | 23.2% | 13.5% | 6.6% | 2.6% | 6.1% |
| Stagnant | 20.5% | 0.0 | 9.9% | 10.9% | 6.0% | 10.1% |
| In-transition | 11.4% | 30.4% | 3.5% | 8.8% | 0.9% | 2.0% |
| | 44 | 56 | 171 | 137 | 117 | 99 |

Source: TIES Survey 2008

*Table 27: ISCO-08 codes by transition trajectory in Amsterdam*

| | ISCO-08 Current Job | | | | | | | | | ISCO-08 Last Job | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Stable | | | Early stable | | | Shifter | | | In Transition | | | Stagnant | | | Inactive | | |
| | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL |
| 1.Managers | 5% | 15% | 12% | 0% | 16% | 10% | 0% | 19% | 9% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% |
| 2.Professionals | 17% | 39% | 32% | 15% | 44% | 33% | 18% | 14% | 16% | 10% | 50% | 17% | 4% | 0% | 3% | 0% | 0% | 0% |
| 3.Technicians and associate professionals | 24% | 18% | 20% | 26% | 18% | 21% | 23% | 19% | 21% | 0% | 0% | 0% | 16% | 13% | 15% | 13% | 0% | 10% |
| 4.Clerical support workers | 24% | 3% | 9% | 7% | 9% | 8% | 5% | 14% | 9% | 30% | 0% | 25% | 16% | 0% | 12% | 13% | 33% | 17% |
| 5.Service and sales workers | 20% | 14% | 15% | 26% | 7% | 14% | 18% | 10% | 14% | 10% | 50% | 17% | 40% | 63% | 45% | 33% | 33% | 33% |
| 6.Skilled agricultural, forestry and fishery workers | 0% | 1% | 1% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% |
| 7.Craft and related trades workers | 2% | 6% | 5% | 15% | 7% | 10% | 5% | 14% | 9% | 10% | 0% | 8% | 8% | 13% | 9% | 4% | 0% | 3% |
| 8.Plant and machine operators, and assemblers | 2% | 0% | 1% | 4% | 0% | 1% | 9% | 10% | 9% | 0% | 0% | 0% | 0% | 0% | 0% | 4% | 0% | 3% |
| 9.Elementary occupations | 0% | 0% | 0% | 4% | 0% | 1% | 23% | 0% | 12% | 0% | 0% | 0% | 12% | 13% | 12% | 17% | 0% | 13% |
| Missing | 5% | 5% | 5% | 4% | 0% | 1% | 0% | 0% | 0% | 40% | 0% | 33% | 4% | 0% | 3% | 17% | 33% | 20% |
| Total | 41 | 101 | 142 | 27 | 45 | 72 | 22 | 21 | 43 | 10 | 2 | 12 | 25 | 8 | 33 | 24 | 6 | 30 |

Source: TIES Survey 2008

*Table 28: ISCO-08 codes by transition trajectory in Strasbourg*

| Table 26.Distribution of ISCO-08 codes byTransition Trajectories across Groups in Strasbourg | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ISCO-08 Current Job | | | | | | | | | ISCO-08 Last Job | | | | | | | | |
| | Stable | | | Early stable | | | Shifter | | | In Transition | | | Stagnant | | | Inactive | | |
| | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL | TR | CG | TOTAL |
| 1.Managers | 0% | 13% | 7% | 7% | 8% | 7% | 0% | 8% | 3% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% |
| 2.Professionals | 8% | 46% | 28% | 17% | 54% | 34% | 6% | 46% | 18% | 0% | 20% | 6% | 0% | 14% | 4% | 0% | 10% | 4% |
| 3.Technicians and associate professionals | 17% | 13% | 15% | 13% | 12% | 13% | 11% | 13% | 12% | 5% | 10% | 6% | 0% | 14% | 4% | 6% | 20% | 11% |
| 4.Clerical support workers | 8% | 0% | 4% | 7% | 8% | 7% | 17% | 8% | 14% | 0% | 20% | 6% | 6% | 14% | 8% | 11% | 0% | 7% |
| 5.Service and sales workers | 14% | 13% | 13% | 20% | 12% | 16% | 23% | 13% | 19% | 29% | 20% | 26% | 17% | 43% | 24% | 6% | 10% | 7% |
| 6.Skilled agricultural, forestry and fishery workers | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% |
| 7.Craft and related trades workers | 11% | 8% | 9% | 10% | 8% | 9% | 6% | 0% | 4% | 5% | 0% | 3% | 0% | 0% | 0% | 6% | 0% | 4% |
| 8.Plant and machine operators, and assemblers | 31% | 3% | 16% | 13% | 0% | 7% | 23% | 8% | 18% | 5% | 0% | 3% | 11% | 0% | 8% | 6% | 0% | 4% |
| 9.Elementary occupations | 11% | 5% | 8% | 13% | 0% | 7% | 15% | 4% | 12% | 33% | 10% | 26% | 61% | 14% | 48% | 6% | 0% | 4% |
| Missing | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 24% | 20% | 23% | 6% | 0% | 4% | 61% | 60% | 61% |
| Total (N) | 36 | 39 | 75 | 30 | 26 | 56 | 53 | 24 | 77 | 21 | 10 | 31 | 18 | 7 | 25 | 18 | 10 | 28 |

Source: TIES Survey 2008